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A Cognitive Approach for an Effective e-Learning System using Learner Personalization Characteristics

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Abstract: The major research in cognitive science is to build an intelligent tutor. The tutor should act as a pedagogical tutor in the e-Learning environment. In all circumstances, the human brain has amazing capability to learn and adapt with respect to the environment. Now a days, the vast and remarkable developments in information and communication technology have prompted many universities, colleges and even students to prefer online learning. Hence, if we use the human brain functionalities to build a cognitive tutor for e-Learning, the entire e-Learning environment becomes similar to classroom learning. Modelling tutor brain called the cognitive tutor should always reflect the pedagogical tutor's behaviour. This study mainly aims at observing the tutor behaviour and how the tutor will notify the student attentiveness, monitor the progress, offer motivation and establish the personal touch with the student behaviour based on the information about the learner personalization characteristics. In learner personalization characteristics, the learner profile and the learning style have been taken to this proposed learning environment. Cognitive architecture ACT-R (Adaptive Control of Thoughts-Rational) has been used to design the cognitive tutor based on the working principles of this architecture.

Key words: Human brain, cognitive tutor, cognitive architecture, ACT-R, e-Learning, cognitive science

INTRODUCTION

Researchers in a web based learning environment have been focusing on the various methodologies to keep the learner as active learner for longer duration and how to deliver an appropriate learning material for them. The traditional distance based learning framework provides a learning resources to the entire learner irrespective of their personalized profile. Technology Enhanced Learning (TEL) is the right platform for an adaptive learning by Oye *et al*. (2012). Recommender system is a software tool which gives a suggestion on the appropriate learning content for the learner based on the learner profile. Learning is a process which has two phases, namely reception and way of processing the information that the learner has received. The reception is nothing but the process of gathering information from various resources and the second phase of learning is an internal activity. The internal activity includes memorization, induction, deduction, introspection, reflection, etc. The entire process of learning is called cognitive style which has unique characteristics for all learners. In 1980's, many colleges, universities and schools started to use a computer in the classroom which initiated research on a computer based learning environment (Brusilovsky, 2001) and it should satisfy the education system needs. The main focus of this study is on how to build an adaptive learning environment.

Buriak *et al*. (1995) developed a learning model for online learning using the various research works on psychology and cognitive science. Learning is the process of retrieving the relevant information for the current situation by integrating their knowledge/behavior. Learning goal should be compatible with a learner's knowledge background, their interest and learning style. All the above all parameters are used to describe the learner personalization. Esichaikul *et al*. (2011) says, research in information and communication technology yields a personalized learning environment to meet e-Learning schemas. LTSA (Learning Technology Standard Committee) defined a IEEE reference model/framework for e-Learning. The main objective of this e-Learning schema should create a personalized learning environment that should provide adaptive learning content. The existing e-Learning environment is accompanied by a static predefined set of interests of the learner.

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Shi *et al*. (2008) describe that the most complicated organ in the universe is the human brain which has unique functionalities. The brain is forever discovering new thoughts, new facts, new principles, etc. Cognitive architecture is a unified cognitive process which addresses the working principles of the human brain and the cognitive model is a program to simulate human behavior. Research in neuroscience addresses the relationship between knowledge and emotion. To design the cognitive model, many prominent architectures like ACT-R-Anderson, EPIC-Mayer, Kiera, soar-Laird, Newell and Rosen bloom are available. ACT-R and EPIC are mainly focused on psychological theories. This study combines the learner personalization characteristics for the purpose of delivering an appropriate learning content based on their behavior while learning. This can be accomplished by cognitive tutor who makes the e-Learning environment similar to classroom learning.

Literature review

e-Learner profile: A personalized learning framework Tzouveli *et al*. (2008), the learner interest helps to form a group and the feedback from one person is considered as a guide note for information delivery for the people in the same group. Personalized learning platform is mainly constructing user profile from their browsing history and user feedback. Esichaikul *et al*. (2011) says, spero system is a sample for LTSA Model, a model includes process, stores and flows. The process is to represent e-Learner as entity, evaluation of their progress, learning course coaching and delivery of an adaptive learning content. A store includes learner performance records and resources of learning materials. A flow is for learner preference, queries, behavior, assessment information, etc. IEEE LTSA Model has been expanded with learner profile and e-Survey. Survey purely follows questionnaires to reflect a learner's knowledge level, learner preference about I/O devices, learning style and physical limitation. Learner history which describes learner browsing history, performance, learner portfolio and learner replies, etc. The difficulty of the spero system is using a large volume of questionnaires which costs more extra work for the user.

e-Learning learning style: Gulbahar and Ayfer (2011), defined learning style is a primary factor to recognize as a medium to reflect the way of learner's learning preferences. The oldest approach of learning style has been proposed by Stafford and Dunn (1993). The learning style differs with respect to the five key dimensions which are learning environment demographic features, social and economic context, emotional condition of the learner, physiological and psychological elements. Kim *et al*. (2013) proposed learning is a process to acquire knowledge which can be created through the transformation of experience. Learner personalization characteristics play a vital role in e-Learning. Examples of personalization parameters are learner profile, distinctive learning style and personal abilities which influences the learner to acquire knowledge and information (Grasha, 1996). Why are many researches going on in e-Learning environment and why are they making learning environment as adaptive? It means that the environment should be attractive, convenient and flexible for scheduling for e-Learner.

Learning style has as many definitions as there are researchers. For instance, we have learning style is a good notation for learner centered approach and ways to enhance teaching and learning experiences. Learning style is a tool to predict the individual's learning behavior while learning which differs from individual and describes the path of learning towards their interest. Lindsay says that to improve the student achievement and satisfaction mutual correlation is required between learning style and teaching style will. Klasnja-Milicevic *et al*. (2011) proposed hybrid recommendation strategy to identify the learner's learning style and proposed a learning platform with learner personalization. El-Bakry and Saleh (2013) defines, learning style is instructional strategy which improves the cognition, context and content of learning. Learning style can be predicted from the behavior of learner like, how people gain knowledge and preserve skills, way of accessing information to help their progress, etc. At the same time, many researches says that learning style doesn't have significant relationship between their behavior and learning styles. In addition to that there is no proof for saying that learning style improves the education performance. In this study, the main objective is to build an adaptive learning environment in all aspects, especially, learner's psychological behavior. Learner's psychological behavior includes learner personalization characteristics. Hence, learning style needs to be included in an adaptive learning environment. To evaluate the statement of Lindsay, two sets of students with the same level of competence were assigned to one instructor. The instructor has taken the same concept in different modes; traditional class room teaching and web based teaching and the knowledge exam was conducted on the same day. The result showed that the possibility of interaction was minimized in web based teaching. Learner personalization is the characteristic of student that can be defined by their unique profile, learning style, personal qualities which influence the capability of acquiring information and interacting with their peers (Grasha, 1996). Generally, learning style is categorized into three groups: visual leaner, auditory learner and kinaesthetic learner. Visual learners see the learning content and then read the content. Auditory learners prefer classroom learning involving listening and speaking. Kinesthetic learners always prefer learning with practical experience. Kolb (1981) describes four ways of learning style.

The diverger, assimilator, converger and the accommodator learning style uses 12 item questionnaires to predict the Learning Style is Inventory (LSI) of the e-Learner. Kolb uses ANOVA (Analysis of Variance) technique to analyze the difference among the groups with the associated procedures. The results of Kolb's learning style can be analyzed by the result of LSI and post learning exam. Next, Dunn and Dunn-school based learning style described by Stafford and Dunn (1993). Dunn approached five dimensions of learning style environmental, emotional support, sociological composition, physiological-perceptual time mobility and psychological elements are globally analyzed and impulsive reflection. Then MBTI's learning style Myers *et al*. (1985) (MBTI) is a psychometric approach. The MBTI questionnaires describe four scales of learning style, namely extraversion/introversion-specifies their level of attention, sensing/intuition-says how the learners prefer to take information, thinking/feeling specifies how learners deal with the external world and judging/perceiving scale describes their knowledge. This scale of learner's learning dimension can be applied into Application (A), Theory (T), Example (E) and Practical exercises (P). Overall impression of this MBTI learning style is measured in the form of low, very low, medium, high and very high. Then Felder Silverman learning style categorizes the learning style into four ways based on 44 questionnaires. In this study, Felder-Silverman learning style is described in an expanded way by including rigid/flexible mode of learning style.

Graf *et al*. (2006) sates, the learner who had minor and moderate impact on their learning style, could manage the available learning content in the learning environment but for those learners who are giving higher value for his/her learning, the environment should give appropriate learning content such as visual learning style. It means that for visual beginner delivering the learning content in the mode of picture, power point based content and verbal learning style display pdf/word based learning content is called for. Graf *et al*. (2007) sates, FSLSM strongly recognizes the learning style with its appropriate ILS value, still the issues in learning style prediction methodology resolves around the investigation about the relation between learning style and its instance, performance and the characteristic of the students. Felder and Silverman describe the score scale in three slab values which are 1-3, 5-7 and 9-11. If the values range from 1-3, then they describe this scored learner as well balanced learner in two dimensions (Pedagogical teaching and e-Learning). For 5-7, the learner is giving a relative preference to the specific dimension and prefer to learn in this teaching environment. For 9-11, the learner has very strong preference for their learning style and the respective learning content. Hence, they are very difficult to face general e-Learning environment.

Table 1: Composition of learning style-(Learner emotion prediction using learning style)

A/R	S/I	B/V	G/Q	F/C
ASBQF	ASVGC	AIVGF	RSVQC	RIVQF
ASBQC	AIBQF	AIVGC	RSVGF	RIVQC
ASBGF	AIBQC	RSBQF	RSVGC	RIVGF
ASBGC	AIBGF	RSBQC	RIBQF	RIVGC
ASVQF	AIBGC	RSBGF	RIBQC	
ASVQC	AIVQF	RSBGC	RIBGF	
ASVGF	AIVQC	RSVQF	RIBGC	

A = Active; R = Reflective; S = Sensing; I = Intuitive; B = Verbal; V = Visual; G = Global; Q = Sequential; F = Flexible; C = Rigid

Linear Discriminant Analysis (LDA) was used to classify the learner, according to their learning style. Felder-Silverman questionnaires were analyzed, if the answer is option A (–value is +1), the learning style belongs to the first set of learning dimension (Active, sensing, visual or sequential and answer is b, the learning style belongs to the second set of learning dimension which is shown in Table 1.

Cognitive tutor: Designing a cognitive model for a real time application should clearly distinguish between two things whether the system is a rule based system or constraint based model. The working principle of rule based model purely depends on the knowledge of the end user and the constraint based model expresses its requirement by raising queries. These queries should meet all the solutions to the problem. These two solutions are nominated for ITS. This system used rule based model to build a cognitive model for e-Learning system because the e-Learning system clearly works to improve the knowledge of the learner. Researchers are modelling the cognitive functions of human brain like thinking and problem solving using rule based concept. Hence, this proposed model uses rule based logic to map the human behavior.

Anderson *et al*. (1990) says, ACT-R is symbolic architecture which has a production rule based framework to model skill learning. Three levels of skill learning are: interactive, compiled and automatic. The working principle of this framework is a rule based and pattern matching with condition action pair system where the given condition is satisfied and the respective rule or action is triggered. Anderson *et al*. (2004), defines ACT-R architecture has two types of knowledge-declarative and procedural knowledge. Two types of storage or access to this knowledge are termed long term memory and short (working) memory. Data structure for this memory is named as a chunk which is the unit of knowledge in working memory. The optimization of the process can be done by the tuning of production rule and the compositing process. Three ways of optimization procedures are used in ACT-R-strengthening, generalization and discrimination.

MATERIALS AND METHODS

Proposed system: In this study, learner profile phase becomes the key process to develop a personalized learning environment. Learner profile entity has four significant parameters which are user unique identification number, preference, history feedback and browsing history. Identity refers to name, age, educational level and languages. Preference refers to their area of interest, decision, knowledge and their learning style. Learner profile data and learner's learning style information are stored in declarative memory of cognitive tutor to retrieve the information in future. User Profile (UP) should have the following (components):

$$UP = \langle id, fh, bh, ls \rangle \quad (1)$$

Id = User unique identification number
bh = Browsing history
fh = Learner feedback history
ls = Learner learning expertise

The profile is constant information about the learner which contains personal data, habits and individual feature. User data can be represented as pair value which reflects the characteristics of the learner with key value.

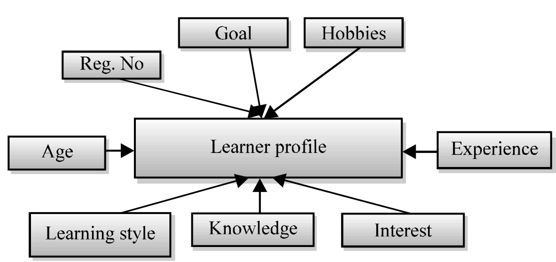

Fig. 1: Learner profile modules

User profiling is an initial phase in e-Learning system which creates user model, modifies and maintains the user details. The abstract form of user profiling is called user model/learner module. Figure 1 describes the basic parameters which are included in learner profile to represent the personal characteristics of e-Learner. The new e-Learner has to register in this proposed e-Learning framework and needs to provide their basic profile information. The profile data should include personal information, portfolio information, performance, goal, login information, learning object and relation information.

A similar profile group of student has been taken for this evaluation. Learner module handles all the information about the learner personal profile and their characteristics. An existing learning environment provides learning content purely based on the profile but the profile is query based survey to depict the learner data, like field entries which may not reflect the actual knowledge of the learner. The 12 categories of learner behavior can be extracted based on the way of approaching the learning environment like mouse clicking, browsing, web log, etc. which are listed in Table 2.

The learner profile data has been grouped which can be done by preprocessing the data based on their knowledge, goal, portfolio information and personal information. This data can be structured into three matrices and the research on data correlation and similarity index has proved that Jaccard coefficient algorithm is always an appropriate one. Hence, we used this to analyze the correlation between the profile data. The mined data is stored in the form of profile database. To assess the student profile, No. of students, learner behavior, duration of studies and their progress can be taken and described as S (Student), B (Learner Behavior) and T (Duration of study) and progress:

$$S = \{Si \mid S1, S2, ..., Sn\}$$
$$B = \{bi \mid b1, b2, ..., bn\}$$
$$T = \{ti \mid t1, t2, t3, ..., tn\}$$

Table 2: Learner behavior in online learning

ID	Learner behavior
LB1	Browse learning goals
LB2	Text learning
LB3	Multimedia learning
Lb4	Practice online
Lb5	Search and view reference
Lb6	Make notes
Lb7	Download courseware
Lb8	Question online
Lb9	Exchange interaction
Lb10	Communication through e-mail
Lb11	Rest or listen to music
Lb12	Talk about QQ when learning

LB:Learner Behavior

The behavioral difference can be calculated as:

$$\nabla b = S1.bi - S2.bi$$

The similarity between the profile data can be measured as:

$$r_{ijk} = \text{Jaccard}\left(S_i.b_k.t_m, S_j.b_k.t_j\right) = \\ | S_i.b_k.t_m \cap S_j.b_k.t_m / S_i.b_k.t_m \cup S_j.b_k.t_j$$

And similarity can be measured by:

$$R_{ijk} = \text{Sim}\left(S_i, S_j\right) = \frac{1}{M}\sum_{k=1}^{M} r_{ijk}$$

Where:
s1 and s2 = Learners
bi = Learner behavior

To meet such issues, this proposed framework always assesses the learner profile by doing test on their knowledge, interest, etc. While testing this in the proposed learning environment, the learner can be categorized with respect to their age. Learner age always helps us to predict learner profile data and their characteristics because the same age group of student behavior or progress will vary from the other range of students:

$$A = \left\{A_i \mid A_1^j A_2^j A_3^j, ..., A_n^j\right\} \quad (2)$$

Where:
A = The age of the list of learner
i = Age of the individual learner
j = Age level

The reason for considering age in the learner profile is that it does affect physical function of human being such as sight, hearing, duration of learning, concentration, etc. but their capability of learning does not change. Always adult learner is faster and more proficient than the older learner. Based on profile analysis, the learner can be categorized into deep learner, application type of learner, inquisitive type of learner and perseverance type of learner. Learner profile survey rates strength and weakness of the learner which given in Table 3. Felder Silverman learning style segments the learner learning style into four dimensions and is presented in Table 4. In this proposed e-Learning framework,

Felder-Silverman Learning style has been chosen to analyze the learner's personality behavior. Felder and Spurlin (2005) say that the positive aspect of FSLSM distinguishes the learner in four dimensions based on their learning style. Felder model uses 44-item questionnaires to predict the learner's learning style using the Index value of Learning Style (ILS). Thomas. A Litinger *et al.* proposed a study experiment on Felder-Soloman ILS to ensure the reliability, its structure, its validity and its response scale. Reliability can be derived from the correlation between the tests score and the actual score. The reliability can be calculated using:

$$r = \frac{\bar{N}\bar{\rho}}{1+\bar{\rho}[N-1]}$$

Where:
N = No. of items
ρ^{-} = Average correlation between items

Chang *et al.* (2009) says that the validity of this ILS is based on the student feedback. The personal preferences of the learner are expressed between +11 and -11 per dimension which means that each dimensions carries 11 questions, ..., for example, +1

Table 3: Strength and weakness of the learner

Learner type	Descriptions
Inquirer	Curious to learn
Knowledgeable	knows many things about the world
Thinker	Thinks before acting
Communicator	Confidently and clearly shares his idea
Principled	Takes the responsibility for his/her actions
Open-minded	Tries and listens to new ideas
Caring	Thinks about the others
Risk-taker	Independent and brave to explore
Balanced	Understands the physical and emotional balance

Table 4: Felder Silverman learning style classification

Learning style dimension	Description
Active/reflective learner	Active learner works actively with the learning material/reflective learner always thinks and reflects their thoughts on learning material
Sensing/intuitive learning	Sensing learner likes to observe the facts and distinct learning material. Intuitive learner always prefers to acquire the summary of the learning content
Visual/verbal dimension	Visual learner always observes the best what they have seen eg., pictures, diagrams and flow-charts/verbal learner can learning content from the textual data in the written or vocal
Sequential/global	Sequential learner always follows a small incremental step with linear learning progress/Global learner uses holistic thinking process in large leaps
Flexible/rigid	Flexible means the learner in positive mood to learn and listen/rigid means not in a mood to mean learn or listen

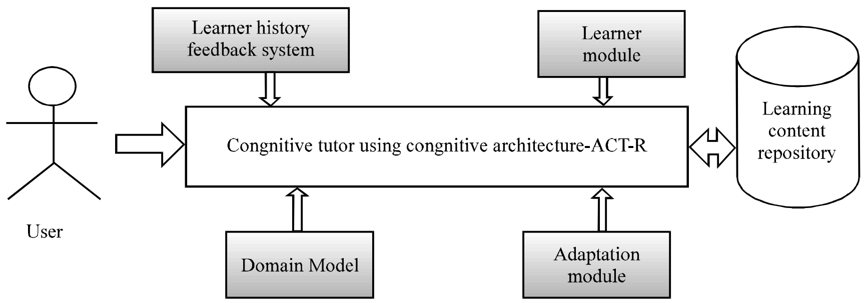

Fig. 2: Proposed system

(answer a) will be added to the index value for active preference and the value decreased by -1 (answer b) for reflective preference.

In addition to that we have included two more learning style called as rigid/flexible. This dimension is purely for those learner who give greater priority to their learning style. For example, as per Felder Silverman learning style all the learners fall into four dimensions. This rigid/flexible describes the emotional status of the learner. If the learner is in rigid mind set-up, they may not express their learning style properly. If the learner is in flexible status, they may clearly answer all the questions of the survey and can express their learning style perfectly. Now the learning style is categorized into five dimensions such as rigid/flexible mode of learning style reflects the learner emotional status while learning and the other four dimension of learning style as per Felder-Silverman learning style.

Figure 2, describe the various segments in e-Learning environment which are learner module, learner history feedback module, domain module, adaptation module and learning content repository. Learner module is the collection of learner profile and learning style repository of e-Learner. Domain model is a collection of learning material which holds the learning content for e-Learner. Learner history feedback module is constantly monitor the system behavior based on the reviews or feedback about the learning environment. Taatgen *et al.* (2006), ACT-R is symbolic architecture which has a production rule based framework to model skill learning. Three levels of skill learning are: interactive, compiled and automatic. The working principle of this framework is a rule based and pattern matching with condition action pair system where the given condition is satisfied and the respective rule or action is triggered. ACT-R architecture has two types of knowledge, declarative and procedural knowledge. Two types of storage or access to this knowledge, long term memory and short (working) memory. Data structure for this memory is named as a chunk which is the unit of knowledge in working memory. The optimization of the process can be done by the tuning of production rule and the compositing process. Three ways of optimization procedures are used in ACT-R, strengthening, generalization and discrimination. The machine learning working principle is rule based learning which categorizes the concept and will match the anticipated destination. John Anderson has defined task specific rule by incorporating general rule knowledge, instruction and experience.

The cognitive model takes the dynamic decision with reference to the Prisoner's dilemma game theory. According to this game theory, it is treated and decided that generally students are in two moods-active mood and non-active mood. The production rule of ACT-R for this situation says that:

- Rule 1: mood, then, continue the lesson
- Rule 2: active mood, trigger an external stimulus to bring the learner to active listening mood

An active function of learner brain is thinking which is classified into functional level, behavioral level and neural level. A design of cognitive architecture should include procedural memory, declarative memory and a goal of the problem.

ACT-R cognitive architecture resembles the human brain structure which may incorporate human psychological behavior into this cognitive architecture to build an adaptive intelligent tutor called cognitive tutor for an effective e-Learning system. The basic working principle of cognitive ACT-R follows:

IF-THEN structure: When the procedural query to check the situation/condition comes to validate a task, the dynamic decision will be taken with respect to the stored information in declarative memory using IF-THEN structure and the respective decision is taken. Learner profile data and learner's learning style information are stored in declarative memory. This information has been properly used by cognitive tutor to deliver a learning content for e-Learner based on learner personal characteristics.

RESULTS AND DISCUSSION

The profile should clearly reflect the knowledge and the learner's interest towards the subject. Learner profile can be assessed by assigning an appropriate learning content based on their behavior and progress can be assessed. The progress of the leaner are evaluated and the results are presented in Fig. 3 which shows that more than 70% of the learner' s knowledge matches their profile and others deviated. There may be the chance to get 30% deviations in their profile and their behaviour. The profile based knowledge analysis has been taken as the primary parameter and this factor should be included into this proposed adaptive learning environment.

This can be improved by triggering related stimuli while learning. Moridis and Economides (2009) proposed various stimuli, stimuli are nothing but a collection of entity which can be used to trigger the learner emotional status from negative mood to active mood. The stimuli are playing its role when the learner is not in a mood to listen; immediately an appropriate stimulus should be raised. Name of the learner, presentation form of learning content, audio, video and picture form of learning content are some of the stimuli. The learning content is delivered by cognitive tutor based on the learner emotional behavior. To evaluate this cognitive based learning environment, two groups of students have been taken and the profile constraints ensured. For group 1 learner, the courses are assigned and their progress is observed and simultaneously group 2 learner undergoes learning adaptively with the help of the cognitive tutor. Cognitive tutor analyzes the learner profile based on the above procedure and stores all the information as chunks for further references. This profile can be retrieved using production rules and progress in profile assessment and depicted in Fig. 3.

When the new user/learner gets into this learning environment, the cognitive tutor analyses the learner characteristics and attitude and then assesses the knowledge and their interest. This preliminary work has been done to refine the proposed learning environment. Next the learning style has to be included in the learner module to process the next level of personalization characteristics of the learner. About 60 students doing their Bachelor's degree in Information Technology were selected and were involved in the learning style prediction methodology using Felder-Silverman learning style along with our questionnaires to predict their emotional behavior.

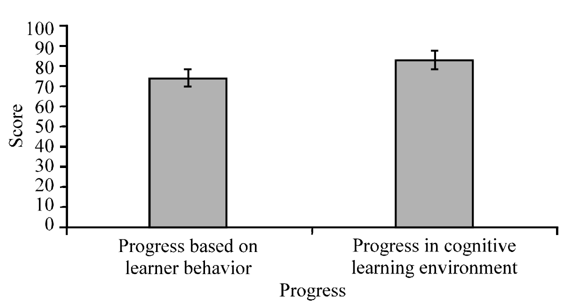

Fig. 3: Profile based learner progress (performance analysis)

For the evaluation of learning style FSLSM, 60 students were chosen and all the students belonged to the same age group and were doing final year B.Tech in Information Technology. There were 34 female learners and 26 male learners and the summary report of all learner's learning style and their progress is represented by the graph Fig. 3. The graph indicates that the set of students have preferred visual based learning style and obviously they preferred visual learning content.

The contribution towards this issue that assigning the relevant type of learning material to the learner with respect to their learning style and evaluating the performance of the learner may help us to conclude how the predicted learning style reflects on their performance.

To evaluate the learner's learning style shown in Fig. 4 for the visual learner, the learning content was delivered in the mode of picture, flow diagram and presentation. Similarly, for all other dimension learners, the appropriate form of learning content was assigned and the progress of the learner was evaluated. If the learner in a particular learning dimension had to face the same type of learning content, he or she should show their better progress.

Then, we have included 11 questions to identify the emotional status of the learner in the form of rigid or flexible mood. We evaluated this 55 questionnaires to predict their learning style and emotional status. To evaluate, we chose PCA (Principal Components Analysis) methodology. The result showed that the learner who was not in a mood to listen might answer the question incorrectly and the 5th dimension was reflected as rigid or flexible. If the learner in flexible status, he/she is in listening mood, else the learner is not in a mood to listen. Hence, the predicted learning style might not be appropriate. We encouraged those students who were in a negative mood by playing motivational videos, motivational videos and made them feel good. After this preliminary process, again we repeated the learning style prediction mythology and we found that 40% of the learners became positive. From this, it is clear that emotional status of the learner plays a vital role during the learning process and depicted in Table 5.

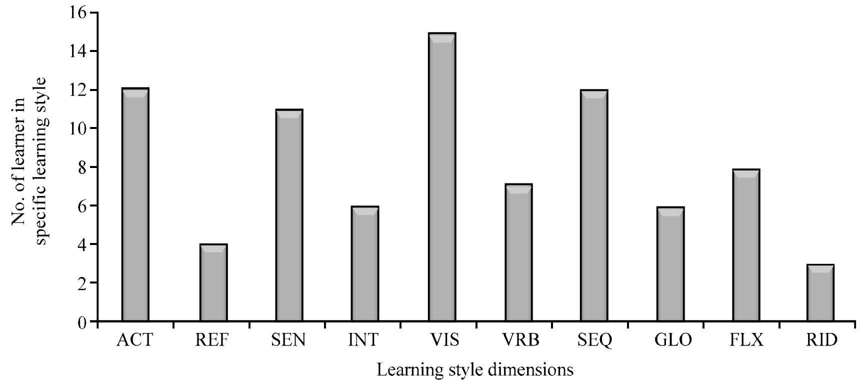

Fig. 4: Predicted learning style

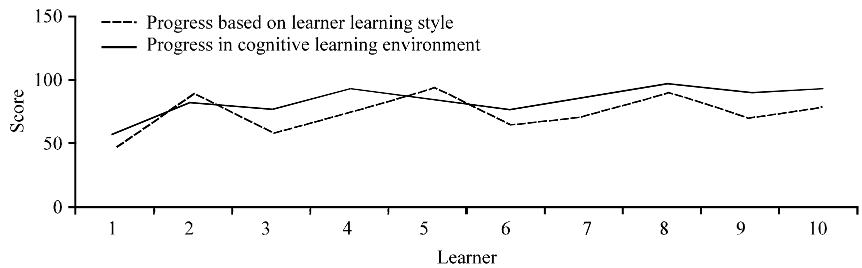

Fig. 5: Learner performance analysis

Table 5: PCA result analysis

Variables	PC1	PC2	PC3	PC4	PC5
Active	0.328518	-0.146150	**0.565165**	-0.191970	0.342759
Reflective	-0.328520	0.146153	-0.465160	0.191974	-0.342760
Sensing	0.136545	**-0.578830**	-0.004460	0.335434	-0.183770
Intuitive	-0.136540	**0.578834**	0.004456	-0.335430	0.183769
Visual	0.290359	-0.143820	**-0.527760**	-0.241010	0.241628
Verbal	-0.290360	0.143823	**0.527763**	0.241015	-0.241630
Sequential	-0.423390	-0.151030	-0.045380	0.190291	**0.509567**
Global	0.423392	0.151032	0.045382	-0.190290	**-0.509570**
Flexible	-0.331460	-0.316380	**0.054848**	-0.506290	-0.175220
Rigid	0.331455	0.316378	-0.054850	0.406292	0.175221

Learning style analysis using PCA method; bold vlaues aresignificant

Still there were deviations in their progress, i.e., nearly 75% of the learners showed their progress and gained their knowledge using their own learning style. 25% of deviation was in learner progress. To solve this issue, after predicting the learner's learning style, the cognitive tutor takes control over the learner by observing their behavior. Based on the deviations in the learner's progress, the tutor keeps the learner in active listening by triggering external stimuli and the cognitive tutor adaptively monitors the behavior of the learner (Esichaikul *et al*., 2011). Now observe the knowledge of the learner can be observed by conducting assessment, after the tutor takes control of the situation. Visible progress is shown; it is nearly 85% which is depicted in Fig. 5.

The working feature of the cognitive tutor was tested and the learning courses are stored in learning repositories. The 20 numbers of students were taken and ensure the same level of their competence, knowledge and their profile and their learning style. The online course on computer programming was assigned and their academic performance was observed by conducting assessment test. The same procedure was repeated for another set of students with the same constraints and their progress evaluated. The progress of this two sample values was analyzed and the results are shown in Fig. 6.

The impact of the stimulus was tested using ANOVA two test. The result showed that when the learner was in a negative mood, it could be resolved by calling by his/her name. This stimulus has an immediate impact and in addition to that playing related video and presentation slide of the learning content has greater the other and reflected in Fig. 7.

Figure 8 is shown feedback about the proposed environment that was collected from the students and graded the learning environment from 5-1 which describes very high to very low. Grade values were analyzed and 78% of the learner showed a very high preference of this learning environment. To Test the feedback of the proposed learning framework by raising questionnaires which are listed in Table 6 can be used.

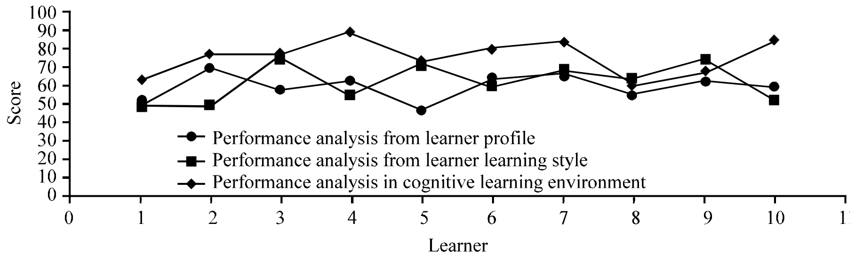

Fig. 6: Performance analysis

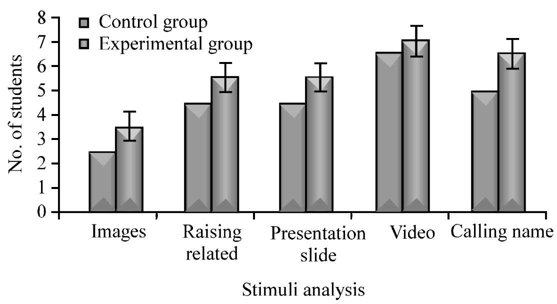

Fig. 7: Stimuli analysis

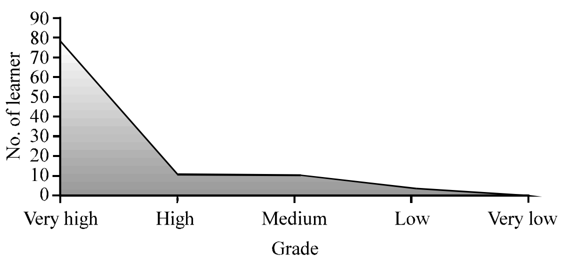

Fig. 8: Feedback grade about the learning environment

Table 6: Feedback form

Adaptive function	Yes	No
Is it an adaptive course format?	✓	-
Is it a correct mood prediction methodology?	✓	-
Is the mood predicted correctly?	✓	-
Have you gained knowledge?	✓	-
Is it a comfortable learning environment?	✓	-
Are you satisfied with the feedback form?	✓	-
Are you satisfied with your profile?	✓	-
Are you satisfied with your predicted learning style?	✓	-
Is it a correct procedure for the evaluation of your progress?	✓	-
Are you satisfied with the cognitive tutor?	✓	-

CONCLUSION

Personalized data about the learner has the empirical impact on e-Learning. The learner's profile and learning methodology have been predicted and the progress of the learner has been noted with respect to their personal information which has been analysed. The cognitive tutor adaptively acts as a pedagogical tutor and monitors online behaviour of the learner. This initial phase of the e-Learning factor helps us a lot to improve the learning environment. An adaptive learning system should take the learner personality into consideration. The personality recognition always chooses the appropriate teaching strategy for learner personality which is considered to develop an interaction with the learner and make it more enjoyable. We have included two more learning attributes to predict the emotional status of the learner in Felder Model. The emotional impact is reflected while observing the data. Feedback about our proposed system has been obtained to evaluate the learning environment. The experiment has been conducted to collect the student impression and the result has shown satisfied for an adaptive education. This emotional prediction is purely a questionnaire based survey. In future, we may add real learner emotion capturing device like brain signal, facial expression or gesture which may reflects the actual emotional condition of the e-Learner.

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